ELSEVIER

Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 38 (2012) 3228 – 3234

Procedia Engineering

www.elsevier.com/locate/procedia

International Conference on Modelling Optimization and Computing- (ICMOC-2012)

Wavelet Based Dynamic Spectrum Sensing for Cognitive Radio under Noisy Environment

Vinit Gupta[a], Abhay Kumar[b] a*

[a]*Medi-Caps Institute of Technology and Manegement, Indore-453331,India*
[b] School of Electronics, DAVV, Indore-452014, INDIA

Abstract

Optimum utilization of available spectra is a major issue of concern in the field of wireless communication technology. Ever growing demand of wireless services poses the problem of frequency scarcity. To improve the spectrum efficiency in order to accumulate more and more users researchers have proposed cognitive radio technology. Cognitive radio, due their adaptive nature adapt themselves as per the available spectrum their by enhancing data transmission, without disturbing other users. The charm of cognitive radio is the spectrum reuse functionality. For cognitive radio environment the primary task is the sensing and identification of spectrum holes in wireless environment. This paper develop a wavelet based efficient spectrum sensing technique for noisy channel with high probability of detection and reduced probability of false triggering. To the best of our knowledge, it is first time that someone has applied the wavelet as a de-nosing tool for improvisation in existing energy detection algorithm for spectrum sensing.

Keywords: Cognitive radio; spectrum sensing; spectrum reuse; wavelet transform; energy detection algorithm..

1. Introduction

Conventional wireless services are based on fixed spectrum allocation methodology which put the constraints like wastage of static spectrum allocation, limited and fixed wireless function resulting in inefficient use of radio spectrum as reported by FCC [1]. Improvement in spectrum efficiency motivates the

* Corresponding author. Tel.: +91-9826564798; fax: +91-0731-2856263.
E-mail address: vinit.gupta66@gmail.com.

1877-7058 © 2012 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2012.06.374

concepts of frequency reuse where the secondary user (SU) are allowed to utilize the radio spectrum allocated to primary users(PUs) when the spectrum is temporally not being used [2].
The concepts of frequency reusability and dynamic spectrum allocation lead to the concept of cognitive radios. The cognitive radio scheme is basically composed following components namely Spectrum sensing, Dynamic spectrum management and adaptive communication. Spectrum sensing mainly refers to sensing and monitoring of the spectrum environment to detect the spectrum holes [3-4]. Dynamic spectrum management means dynamic selection of best available band for communication. Adaptive communication means adaptive configuration of transmission parameters for opium utilization.
Spectrum sensing is a primary issue in cognitive radio environment. Spectrum sensing is associated with probability of false triggering. High probability of detection results in better protection of primary users. Lower probability of false triggering results in optimum reuse of channel when available, thereby providing the higher throughput for secondary users [5-6]. In this work an effective wavelet based spectrum sensing algorithm is presented with an objective to maximize the throughput for secondary users by reducing the probability of false triggering, under the constraints of primary user protection and noisy channel.
De-noising is to decrease noise levels at the same time as the signal degradation is minimized. As noise is found in all over the place and usually corrupted with signals, de-noising is essential and useful in many engineering applications. Along with the offered de-noising algorithms, wavelet de-noising algorithms are the most frequent approaches for de-noising because wavelets exploit both the time and the frequency domain information of signals and therefore wavelet de-noising approaches can achieve good performances. In the past, many researchers studied the effects of various thresholding functions on the de-noising performances [7]. Nowadays, soft thresholding wavelet de-noising methods are well understood and usually applied to everywhere.

The remainder of the paper is organized as follows. In Section II, wavelet fundamentals are briefly described and basic principles of de-noising are explained. Section III described wavelet based modified energy detection algorithm for spectrum sensing. Simulation results are shown in Section IV, with conclusions drawn in Section V.

2. Wavelet Fundamentals

The concept of wavelet analysis has been developed since the late 1980's. Wavelet analysis is powerful and efficient tool for time-frequency analysis. First, a mother wavelet is chosen i.e. a function subject to some condition like mean-value 0. Instead of using pure harmonics as in Fourier analysis, wavelets use shifted and dilated version of the mother wavelet. By using a two variable base: one for the translation and other for dilatation; we can introduce enough redundancy to maintain the local property of the original signal [8].

2.1. Discrete Wavelet Transform

DWT is designed from the multi-resolution analysis that decomposes the given signal space into a approximate space,V, and detail spaces, W, as shown in equation (1).

$$V_{j+1} = W_j \oplus V_j = W_j \oplus W_{j-1} \oplus V_{j-1} \tag{1}$$

where Wj is the orthogonal complement of Vj in Vj+1 and □ represents the orthogonal sum of two subspaces. Two spaces, Vj and Wj are constructed by orthonormal scaling functions, $\phi_{j,k}$, and orthonormal wavelet functions, $\psi_{j,k}$, respectively. Scaling function $\phi_{j,k}$ and wavelet function $\psi_{j,k}$, are obtained as shown in equation (2).

$$\left.\begin{aligned} \phi_{j,k}(t) &= 2^{j/2}\phi(2^j t - k) = \sum_l h_{l-2k}\phi_{j+1,k}(t) \\ \psi_{j,k}(t) &= 2^{j/2}\phi(2^j t - k) = \sum_l g_{l-2k}\phi_{j+1,k}(t) \end{aligned}\right\} \tag{2}$$

with high-pass filter, $g_{l-2k} = \langle\ \psi_{j,k}\phi_{j+1,l}\ \rangle$ and low-pass filter, $h_{l-2k} = \langle\ \phi_{j,k}\phi_{j+1,l}\ \rangle$. $\langle\ \rangle$ means inner product. Using these functions, DWT of a given signal, f, provides scaling coefficients and wavelet coefficients. The scaling coefficient at the j^{th} level k^{th} time is computed by [8-9]:

$$c_{j,k} = \left\langle f, \phi_{j,k} \right\rangle = \sum_l h^*_{l-2k}\left\langle f, \phi_{j+1,l}\right\rangle = \sum_l h^*_{l-2k} c_{j+1,l}$$

The wavelet coefficient at the jth level and kth time is

$$d_{j,k} = \left\langle f, \psi_{j,k} \right\rangle = \sum_l g^*_{l-2k}\left\langle f, \phi_{j+1,l}\right\rangle = \sum_l g^*_{l-2k} c_{j+1,l}$$

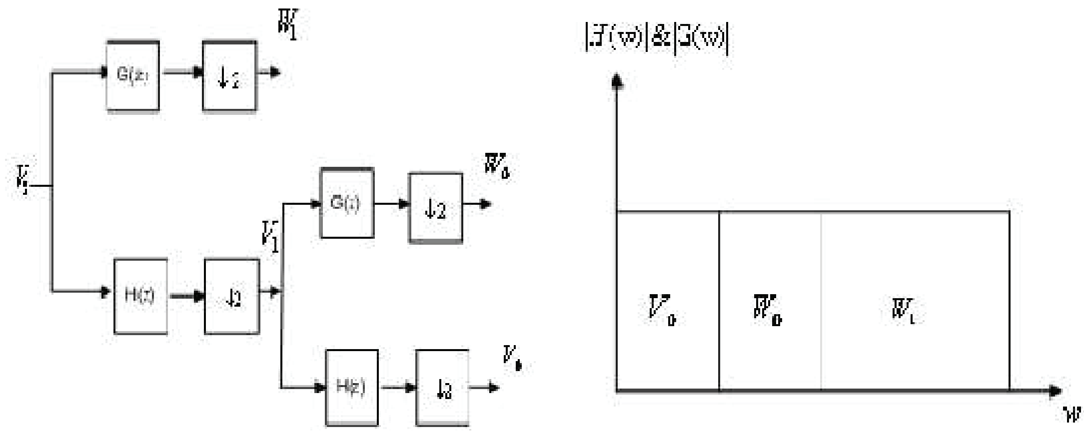

Fig.1 (a) 2-level decomposition; (b) 2-level frequency separation property.

Figure 1(a) and (b) show 2-level analysis part of the DWT and its frequency separation property.

2.2 Wavelet De-noising

Removing noise components by thresholding [7] the wavelet coefficients is based on the observation that in many signals; energy is mostly concentrated in a small number of wavelet dimensions. The coefficients of these dimensions are relatively large compared to other dimensions or to any other signal (mainly noise) that has its energy spread over a large number of coefficients. Thus, by setting smaller coefficients to zero, one can nearly optimally reduce noise while preserving the important information of the original signal [10].

Let T denote the given threshold. The soft thresholding is defined by

$$y = \begin{cases} sign(x).(x - |T|) & |x| > T \\ 0 & |x| \leq T \end{cases}$$

For the hard thresholuding

$$y = \begin{cases} x & |x| > T \\ 0 & |x| \leq T \end{cases}$$

There are two types of thresholding techniques hard thresholding and soft thresholding. In hard thresholding all coefficients below a predefined threshold value are set to zero. But, in soft thresholding where in addition the remaining coefficients are linearly reduced in value. So here in this method soft thresholding is applied with sure selection rule. Note that the range over which the SURE threshold is considered is based on a maximum value equal to the universal threshold, so that the SURE threshold is always less than the universal threshold. Thresholding can be done universally across all wavelet decomposition levels, referred to as level-independent thresholding, or else the threshold level can be varied at each level, level-dependent thresholding [10-13].

3. Spectrum Sensing via wavelet based energy detection algorithm

Energy detection algorithm is one of the simple and effective schemes among the various spectrum sensing techniques. The objective is to identify the channels occupied by the primary user by the analysis of the energy in each identified channel. The main drawback of energy detection scheme is that it can't distinguish between noise and energy of the signal. In case of white noise the detector told that primary user is present all around the spectrum, especially for low SNR signals.
In this work, wavelet based de-noising algorithm is applied prior to energy detection algorithm; in order to avoid false estimation of spectrum holes. Normally the signal transmitted through the channel is corrupted by the noise.

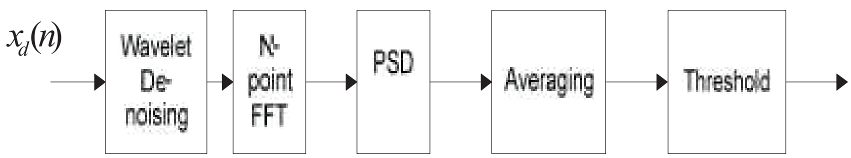

Fig. 2 Implementation of wavelet based energy detector.

Let $x_t(n)+\sigma(n)$ is the signal transmitted over the channel. Where $x_t(n)$ is the signal and $\sigma(n)$ is the channel noise sample presence of noise makes cause false triggering at the detector end. In order to avoid false triggering the received signal is first de-noised using wavelet based sure algorithm. After de-noising the conventional energy detection algorithm is applied to remaining signal.
Firstly, in each time slot, a block of signal samples are segmented into T frames. Denote tth frame of the input samples by $x_t(n)$, $n = 0,1,.....,N-1, t = 0,1,......,T-1$, where N is the number of samples in a frame, and T is the number of frames .Then the segmented frames are multiplied by a window function as described in equation (3).

$$x_{w,t}(n) = x_t(n)w(n) \qquad n = 0,1,.....,N-1, t = 0,1,......,T-1 \tag{3}$$

After that, FFT is applied to the windowed frame (equation 4). Note that $x_{w,t}(n)$ are real numbers and the frequency spectrum of $x_{w,t}(n)$;

$$X_t(k) = \sum_{n=0}^{N-1} x_{w,t}(n)e^{-j2\pi kn/N} \qquad k = 0,1,.....,N-1, t = 0,1,......,T-1 \tag{4}$$

is symmetric, thus for each frame only $\frac{N}{2}+1$ tones of

$X_t(k), k = 0,1,.....,N/2, t = 0,1,......,T-1$,

are required (assume N is even). These tones are separated by f_s / N Hz.
The power spectral density (PSD) calculation follows the FFT operation. Define $p_t(k)$, the PSD of $x_{w,t}(n)$, as:

$$P_t(k) = \left|X_t(k)\right|^2, \qquad k = 0,1,...,N/2, t = 0,1,...,T-1 \tag{5}$$

The PSDs of T consecutive frames are used for averaging, yielding:

$$P_{avg}(k) = \frac{1}{T}\sum_{t=0}^{T-1} P_t(k), \qquad k = 0,1,......,N/2 \tag{6}$$

Where the factor 1/T is not actually required. Let P_m be the mean of $P_{avg}(k)$ calculated across all frequency tones:

$$P_{mean} = \frac{2}{N+2}\sum_{k=0}^{n/2} P_{avg}(k), \tag{7}$$

Where, again, the factor 2/N+2 can be dropped. In order to be robust to the noise level, the decision variable D (k) is formed as a ratio:

$$D(k) = \frac{P_{avg}(k)}{P_{mean}}, \quad k = 0,1,........,N/2 \tag{8}$$

Finally, thresholding is applied to $D(k)$ for k=0,1,….,N/2, and the decision on channel states are made according to the following rules:

- Occupied if $D(k) > \beta$
- available if $D(k) < \beta$

where β is a threshold parameter.

4. Simulation

In order to illustrate the proposed scheme a simulation study is carried out with twenty primary users in the spectrum span of 20-40 MHz. signals transmitted over the channel are assume to be corrupted by Random Gaussian noise. First conventional energy detection algorithm is applied for spectrum sensing the results are shown in figure 3(a). As its clear from figure that there is incorrect information about spectrum usability as particular spectrum span is not utilized by primary user but there is a indication of power in that particular span. This false triggering is due to noise signal and this aspect limits the effectiveness of the conventional energy detection algorithm.

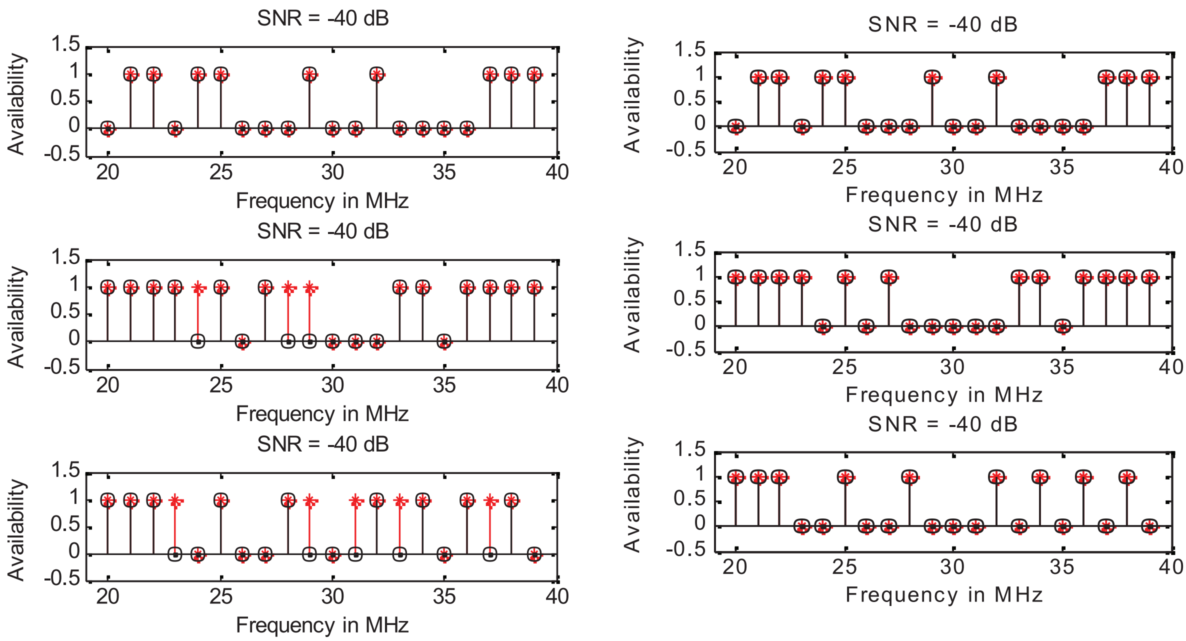

Fig.3 (a) Spectrum sensing with conventional energy detection algorithm; (b) Spectrum sensing with modified energy detection algorithm

.

Secondly the modified energy algorithm is applied to the same signal. In this work, a wavelet based soft thresholding technique is used. Mother wavelet used is DB8 and the algorithm applied is heursure. As clearly, indicated by the figure 3(b). Due to de-noising feature incorporated in conventional energy detection algorithm. Probability of false detection is greatly reduced.

5. Conclusion

Spectrum sensing is a critical component of the emerging opportunistic spectrum access system. Low probability of false estimation of spectrum holes results in optimum usability of channel resources. In this work we have explore the effectiveness of wavelet based modified energy detection algorithm for spectrum sensing. As clear from simulation carried out, the modification applied detects and suppress the noisy power and thus relaxes the constraints of false identification of spectrum holes due to noisy channel, thus maximize the throughput for secondary users.

References

[1] [1] Federal Communications Commission, “ Spectrum Policy Task Force ” , Rep. ET Docket no. 02-135, Nov. 2002.

[2] S. Haykin, “Cognitive radio: Brain-empowered wireless communications,” IEEE J. Selected Areas Communications, vol. 23, no. 2, pp. 201-220, Feb. 2005.

[3] J. Mitola and G. Q. Maguire, “Cognitive radios: Making software radios more personal,” IEEE Pers. Commun., vol. 6, no. 4, pp. 13-18, Aug.1999.

[4] Budiarjo, I., Lakshmanan, M. K. & H. Nikookar (2008). Cognitive Radio Dynamic Access Techniques. In Wireless Personal Communications, Volume 45, Number 3 / May, 2008, Springer Netherlands

[5] D. Cabric, S. M. Mishra, and R. W. Brodersen, “Implementation issues in spectrum sensing for cognitive radios,” in Proc. 38th Asilomar Conf. Signals, Syst., Computers, Nov. 2004, vol. 1, pp. 772-776.

[6] Y.-C. Liang, Y. Zeng, E. Peh, and A. T. Hoang, “Sensing-throughput tradeoff for cognitive radio networks,” in Proc. IEEE Int. Conf. Commun.(ICC), June 2006, pp. 5330-5335.

[7] D.L. Donoho, “De-noising by soft-thresholding”, IEEE Trans. on Information Theory, vol. 41 no. 3, May 1995, pp.613-627.

[8] G. Strang, T. Nyugen. “Wavelets and Filter Banks”, Wellesley/Cambridge Press, 1996.

[9] S. Mallat. “A wavelet tour of signal processing”, 2nd ed. Academic Press, 1999.

[10] F. Luisier, T. Blu, and M. Unser, “A new SURE approach to image denoising: Inter-scale orthonormal wavelet thresholding,” IEEE Trans. Image Process., vol. 16, no. 3, pp. 593–606, Mar. 2007.

[11] Zhi Tian, Georgios B Giannakis, “A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios”, IEEE 1st Int. Conf. on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM),pp.1-5,2006.

[12] Thierry Blu, and Florian Luisier “The SURE-LET Approach to Image Denoising”. IEEE Transactions On Image Processing, VOL. 16, NO. 11, pp 2778 – 2786, NOV 2007.

[13] X.-P. Zhang and M. D. Desai, “Adaptive denoising based on SURE risk,” IEEE Signal Process. Lett., vol. 5, no. 10, pp. 265–267, Oct. 1998.